AN AUTONOMOUS MISSION MANAGEMENT SYSTEM TO ASSIST DECISION MAKING OF A HALE OPERATOR

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Abstract
Operating at an airspeed of about 30 m/s at an altitude of 18 km, solar powered, unmanned, high altitude pseudo satellites (HAPS) are a good alternative to satellites to provide surveillance and communications services. Being generally constructed as an ultra-lightweight unmanned fixed-wing aircraft, HAPS are sensitive to critical weather conditions. Our work consists of developing a hybrid mission management system, equipped with a human machine interface and a decision assistant, to aid the HAPS operator in choosing the 'best' plan analytically. In this work, real weather forecast data from the past is integrated and used in the hybrid mission management system.
Keywords: mission planning, UAV, HAPS, weather, decision making

1. INTRODUCTION

The primary motivation of this article is to optimize the planning for high altitude long endurance (HALE) platforms contracted to carry out surveillance missions with an electro-optic mission camera. The considered HALE is a solar powered, fixed wing, ultra-lightweight (~100 kg) unmanned aerial vehicle (UAV) operating at an altitude of ~18 km at a speed of ~30 m/s to provide satellite-like services like communication and surveillance. HALE platforms can be promising alternatives for satellites in civilian and military use. A HALE platform used for such application is sometimes also referred to as a high-altitude pseudo satellite (HAPS). However, due to the properties of the platform, diverse weather conditions must be considered in the operation, making the mission planning much more complicated.

A HAPS is currently operated by four crew members, in charge namely of mission planning, flight control, sensor operation and data assessment. To make the technology economically viable, it is necessary to increase the autonomy of the mission management system (MMS) in order to reduce man power while maintaining the balance between mission success and flight safety.

Considered in this work are surveillance missions of desired locations of interest (LOIs), which must be carried out by the HAPS with an electro-optic camera. Based on the mission tasks and mission constraints, the MMS generates multiple flight plans within the allowed planning time. The flight plans are computed by taking the weather conditions such as cloud and wind into account. The calculated plans will be evaluated analytically by a decision-making tool based on a set of parameters given by the operator. The HAPS operator receives results in form of a ranking list and selects, according to the situation, the most appropriate mission plan.

The final output consists of a feasible flight path with sequences of waypoints that will be transmitted to the on board automatic flight management system. The plans are generated and tested using the properties of a HAPS.

The paper is structured as follows. Section 2 describes the problem space and the example missions considered in this work. Section 3 gives an overview of the available realistic weather data that are integrated and considered in the MMS. The design of the hierarchical task scheduler/planner is presented in section 4 and subsequently, the decision assistant is presented in section 5. The interaction of the operator with the human machine interface of the simulator is described in section 6. The final conclusion of this work is included in section 7.

2. PROBLEM DEFINITION

The work in this article is based on a realistic mission environment as real weather data is used. Considered is a HAPS carrying out its missions at a constant optimal true air speed (TAS) at a constant operation altitude. A realistic mission scenario is shown in Fig. 1. The missions are carried out by a single HAPS during daytime. The platform has the properties mentioned in the introduction: lightweight, solar powered, long endurance cruising ability and relatively low air speed. It is assumed that the HAPS gains more energy than it consumes during daytime. The feasibility study of the mission planning in this work is limited to offline long-term mission planning, i.e. the plan is computed for a long-term mission before execution.

Examples of surveillance missions a HAPS can execute are border control, forest fires monitoring, whirlwinds tracking etc. Fig. 1 shows an example of different surveillance missions. The locations of interest (LOIs) are represented by the green polygons. These are areas that the contracting clients wish to monitor. Neighbouring LOIs of a single client are grouped together and encompassed in an allocated airspace, i.e. the mission area (MA) that is represented by the blue polygons. The HAPS is free to operate within the MA's. The yellow rectangles outline the waiting areas (W1 and W2). These areas must be accessible for the time the HAPS is not in use to fulfil missions. Corridors between MAs and waiting zones are negotiated and approved by the air traffic control.

To carry out upcoming missions, the crew of the HAPS needs to plan the flight path (order of LOIs). The planning process considers the knowledge of the weather situation within the operating airspace of the HAPS during the mission execution. Under the consideration of mission- and platform-specific constraints, the manual analysis of all weather data is too time-consuming for the crew. Therefore, the support from an automated mission management system (MMS) to generate feasible flight plans is necessary. The mission management system shown in this work is intended to reduce the workload of the operator.

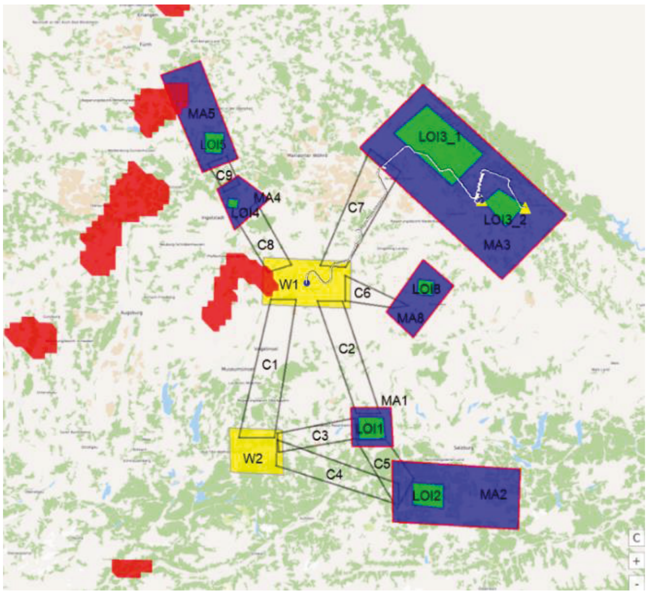

FIGURE 1. Mission scenario map with a partial flight path

3. WEATHER DATA

Due to the lightweight structure of the HAPS and mission constraints, the consideration of weather information (long-term forecast and regular updates of weather forecast) is necessary for planning a mission. This section provides an overview of the weather data in used. Unlike static obstacles like uneven terrain, hazardous weather zones vary over time and are described by moving polygons which also deform over time. Hazardous weather conditions are clouds, strong wind, thunderstorms and turbulences, which have immense effects on the flight behaviour, could even impede the platform if ignored during operation.

TAB 1 shows the used weather data and the provided forecast durations. The recorded weather data are available either in 2D or 3D at each time instant. The 2D data assumes that the measurement is identical over all altitude levels. The forecast set describes the number of predicted forecast hours. Using an example weather data like the Cb-LIKE with a forecast set of one to six. The data includes forecast for the upcoming six hours.

The weather data are stored in comprehensive XML-formatted text files [12]. The corresponding updating rate for each data set is illustrated in Fig. 2

One of the greatest hazards for HAPS are the cumulonimbus clouds (Cb). A Cb cloud can easily achieve an expansion of over nearly the entire vertical atmospheric layer [9]. The Cb clouds contain water, and icing, as well as thunder and lightings. Therefore, a safety distance between Cb clouds and platform must be kept. For the simulation of these type of clouds the data of the Cb-LIKE (**C**umulonim**b**us-**LIKE**lihood) algorithm [12] is used. With a coverage of Germany and sections of neighbouring countries, the clouds are shown as polygons consisting of several longitude and latitude vertices. Each update of data set consists of one to six forecast sets (i.e. Cb-polygons are forecasted up to six hours into the future). Each forecast set comprises up to five threshold sets, where the higher the threshold value, the more likely a cloud polygon becomes a thunderstorm. In Fig. 1, the red polygons represent the Cb-LIKE objects.

Type of weather data algorithm	**Dimension**	**Forecast set per update**
Cb-LIKE	2D	1 to 6
Cb-Tram	2D	0 to 1
Wind field (NoGo-Areas)	3D	21
Cloud coverage	2D	21
Wind velocity	3D	21

TAB 1. Weather data

Another algorithm to show thunderstorms and Cb polygon cells is Cb-Tram (**C**umulonimbus **TR**acking **A**nd **M**onitoring). The data compiled with the Cb-Tram algorithm, includes three different developing states of intense convective thunderstorms [12]. The forecast horizon is one hour with an update rate of five minutes.

Besides the clouds, the wind also has a significant influence on the flight dynamics of the UAV. The real wind data used is taken from COSMO-DE [12], a model data developed by the German Meteorological Service (DWD), with a forecast horizon of 21 hours and eight updates per day. The grid mesh size has a horizontal resolution of ~2.8 km and contains 50 vertical layers [11]. New updates are available every three hours. For each forecast set, the wind vector is expressed in terms of three wind components based on the numerical *Arakawa*-C-Grid [11]. The U wind component represents the zonal velocity (the wind towards east), the V wind component represents the meridional velocity (the wind towards north) and W represents the vertical velocity.

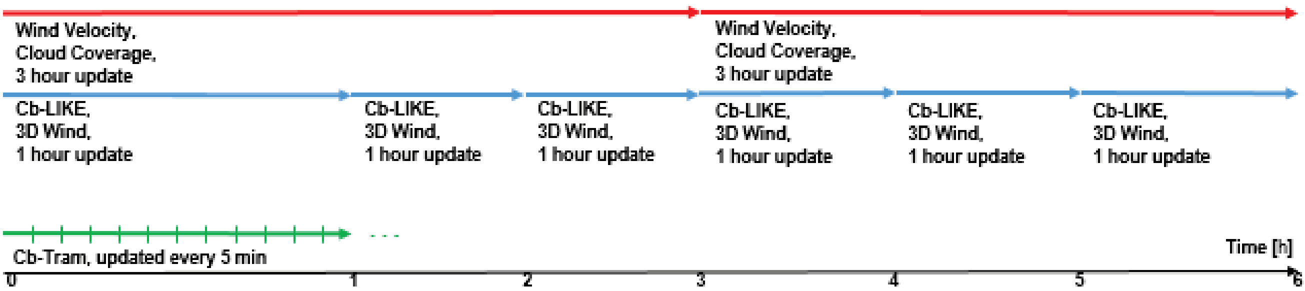

FIGURE 2. Timeline of the weather data update frequency

On the map of the human-machine interface on the ground control station, the wind velocity is represented by wind barbs (Fig. 7), which is a concise way of representation [9]. To understand the wind data displayed, it is important to note that the wind barb points to the direction the wind originates and the wind arrow to the direction the wind blows. Since wind vectors are provided for 50 different airspace layers (from 10 m to 21500 m over the ground), only a selected layer will be displayed on the human-machine interface. The operator can select the layer to be shown and adjust the resolution of displayed wind barbs.

Another form of wind data is represented by the three-dimensional wind no-go areas (3D-Wind field). The term “no-go area” denotes a region which should be avoided by the UAV. This set of data stores wind objects in form of polygons which represent areas with a certain wind strength [11]. Threshold sets range between 2.5 to 40 m/s in 15 different flight levels. Since the wind no-go areas are derived from the COSMO-DE data, the weather data has a forecast horizon of 21 hours.

Similar to the wind velocity data made available by COSMO-DE, cloud coverage data has a forecast horizon of 21 hours and are updated every three hours, as shown in Fig 2. The data includes information on the cloud coverage in form of percentage for each grid point.

Given the complexity due to the dynamic weather conditions, the HAPS operator faces the challenge of finding the long-term ‘best’ feasible flight path to fulfill the missions. Coupled with a Markov decision process (MDP) based policy generator, a hierarchical task scheduler/planner can compute feasible and promising plans much faster than a HAPS crew member can. These plans will be presented to the operator. The ‘best’ plan among the suggested plans will subsequently be selected by the operator with regard to reward, risk, weather situation and execution time.

4. HIERARCHICAL TASK SCHEDULING AND PLANNING

As the light-weight HAPS is a fixed wing platform equipped with solar panels to ensure energy supply and with a very week electro-motor for an economical energy consumption, the HAPS has very restricted motions, making it more difficult to follow any random path, especially in a wind field. Therefore, many conventional flight path planning methods such as the Dubins [8, 13] path cannot be applied for HAPS. Many existing planners deal with the kinodynamic constraints by considering the effects of the control inputs of the vehicle [6, 15]. By doing so, the wind effect on the kinematics of the HAPS can be easily taken into account.

However, such action-based discrete-time planner uses a search function that grows exponentially with the number of search nodes. Since the operating area involved is in the order of magnitude of 100 km, it is almost impossible to determine a flight path in due time that complies with the kinodynamic constraints of the HAPS while avoiding obstacles (areas with critical weather conditions) and considering mission optimality. A rather intuitive method to reduce the search space of the planning problem is to adopt a hierarchical planning/scheduling approach by decomposing a plan from a higher abstraction level into lower abstraction level plans [7].

As described in the work from Kiam and Schulte [7], the abstraction levels can be ordered according to the dimension of the mission elements as shown in Fig. 3. The surveillance mission is first decomposed into subtasks to determine the order of the mission areas to monitor (MA-level). Inside each mission area, the ordering of the locations of interest is decided (LOI-level), and subsequently, the flight pattern (P-x) for each location of interest as well as the start point (SP-x) of the flight pattern (FP-level). Once the flight patterns are determined, waypoints to fly can be computed based on the field of view of the camera, as long as the flight path in the wind field is kinematically feasible.

The first three abstraction levels involve logical planning approach while the flight paths (represented by sequences of waypoints) are computed with an analytical planner.

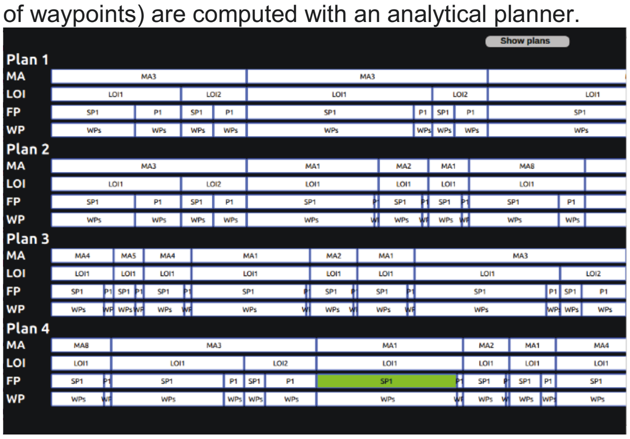

FIGURE 3. Hierarchical planning and scheduling

4.1. Logical Scheduling

The logical scheduling for the first abstraction levels consists mainly of deciding the order in which the tasks have to be carried out (see Fig. 3). Figure 4 shows an example of determining the order of mission areas to fly to. The HAPS can either first fly to MA1 and then to MA2 or vice-versa. The order of MA to fly is decided manly based on cloud coverage and time frame for mission success.

Since the mission success rate is probabilistically correlated to the cloud coverage, Markov decision process (MDP) provides a convenient method to decide for the order in which the monitoring of the mission areas should be carried out. Kiam and Schulte [7] uses the *k-best policies* [2] to determine more than one plans with the most promising expected rewards.

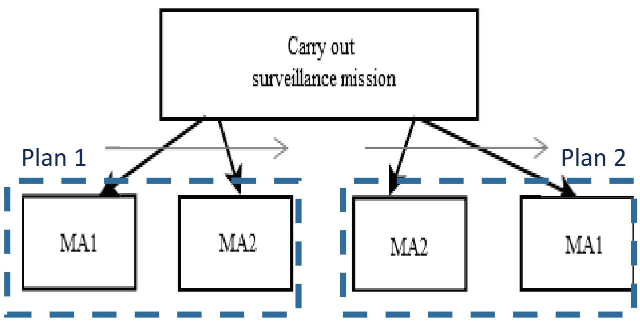

FIGURE 4. Mission area abstraction level in hierarchical scheduling

4.2. Analytical Planning

The last abstraction level consists of planning for the flight path from a start position to a goal position while avoiding obstacles that represent hazardous areas in the airspace and while considering the kinodynamic constraints of the HAPS. The start and goal positions are given by the logical scheduler, since the logical scheduler dictates which mission element to fly to next.

The path planning is carried out using the method described in [10]. The influence of the wind on the velocity of the HAPS relative to the ground in the inertial North-East-Down frame $v^g = (\dot{x}^g, \dot{y}^g, \dot{z}^g)$ is given by

(1) $$\dot{x}^g = v^a \cos\psi \cos\theta + w_x^g,$$

(2) $$\dot{y}^g = v^a \sin\psi \cos\theta + w_y^g,$$

(3) $$\dot{z}^g = -v^a \sin\theta + w_z^g,$$

where $v^a$is the optimal airspeed of the HAPS, ψ and θ are respectively the yaw and pitch angle and w_*^g is the wind speed.

The yaw rate is limited by the speed as well as the turn radius of an aircraft.
$A_\psi = \{-|\dot{\psi}_{max}|, -|\dot{\psi}_{max}| + \epsilon_{\dot{\psi}}, \dots, |\dot{\psi}_{max}| - \epsilon_{\dot{\psi}}, |\dot{\psi}_{max}|\}$ and $A_\theta = \{-|\theta_{max}|, -|\theta_{max}| + \epsilon_\theta, \dots, |\theta_{max}| - \epsilon_\theta, |\theta_{max}|\}$ represent respectively the set of acceptable turn angles and acceptable climb angles. These sets also denote the feasible actions that can be considered as control inputs of a control-based planner like the RRT-planner from the Open Motion Planning Library [6] or a domain independent planner like the Expressive Numeric Heuristic Search Planner (ENHSP) [4].

4.3. Hierarchical Plans

The hierarchical scheduler/planner suggests several feasible plans. Fig. 3 shows the plan suggestions. The black route in Fig. 1 displays the selected partial flight plan highlighted in green in Fig. 3 of the abstraction level “Flight Pattern (FP)”.

Several complete plans will be provided within the allowed planning time using the MDP-based *k-best policies [2]*. The plans in Fig. 3 for example are depicted in the order of optimality ranking at the “MA” abstraction level. Generally, the optimization is more approximative at a higher abstraction level than at a lower abstraction level, since the state space of the higher level scheduling is more abstract or rather more simplified. Therefore, the optimality ranking of the higher-level plans might not be aligned with the optimality ranking of the lowest-level plans.

An analysis is required at the waypoint abstraction level to better rank the suggested plans to help the HAPS operator make the final decision. Furthermore, by performing a profit/risk analysis of the resulting plan suggestions posterior to the scheduling/planning, one gains more flexibility in the sense that the operator is free to define the risk factor to rank the suggested plans based on how much risk he is willing to accept. The following section describes the decision assistant used for a reward/risk analysis to help the operator choose the best feasible plan among the given plan suggestions.

5. DECISION ASSISTANT (DA)

Several plans are suggested by the scheduler/planner as shown in Fig. 3. These plans differ in the order of tasks to execute and hence the flight paths and execution time elapsed. Different profit and risk can ensue depending on which plan is selected.

In this work, we consider an operator in-the-loop decision-making system. The final decision to select the best plan among the suggestions lies in the hands of the operator in order to maintain a high level of situation awareness [14].

A decision assistant (DA) is developed in the frame of this work as an analytical support to help the operator select the best plan. Using parameters set by the operator, the decision assistant computes analytically the profit as well as the risk of the operation and returns a ranking of the plans. Besides aiding the operator to decide at the beginning of the operation, the decision assistant also acts as a continuous monitoring tool to check and rank the plan suggestions according to the latest weather updates between the computation of the plans and the selection of the ‘best’ plan to execute. The ranking of the plans can change during the course of the operation since the plans recommended by the MMS are computed with forecast weather data at the planning time and these weather data are regularly updated (see Fig. 2).

In order to find the best plan among the suggested plans as shown in Fig. 3, the plans have to be assessed using up-to-date weather data. The assessment is performed by computing [3]:

- the profit of each plan, which consists of the reward for successful missions, modulo the operation cost,
- the crash risk of each plan to account for the risk of a crash due to hazardous weather conditions or low energy level.

The planning problem for surveillance mission of a HAPS is a multi-objective optimization problem, in which one regards a maximization problem (reward) and a minimization problem (risk), along with constraints on each function. In general, an optimal solution does not always exist and a reasonable trade-off among the objectives has to be considered [1]. Before proceeding to determine a ranking, the used objective functions and their contributing factors have to be defined.

5.1. Objective Functions

The operator needs a ranking of all the possible plans. Considered in this work are the profit and risk of each plan. The following subsections describe how they are determined.

5.1.1. Profit

In our example mission scenario, the HAPS is used to accomplish civilian client’s orders, therefore the commercial profit of the operation is important. To maximize the profit, the operator has to find the plan with the optimal margin between cost and reward. The total profit of a plan can be determined with the following function:

(4) $$f_{\text{profit}}(plan) = \sum_{i=1}^{n_{\text{MA}}} R_i * ms_i - (t_{\text{out},i} C_{\text{out}} + t_{\text{in},i}\, C_{\text{in}}),$$

where R_i is the reward paid by each customer for each fulfilled mission, ms_i is the mission success that takes 1 as value if the forecast cloud coverage is less than 30% and 0 otherwise (see section 3).

The last term of the profit function shows the operation cost that has to be subtracted from the reward. C represents the hourly operation cost of the HAPS. There are however two different costs: C_{out} describes the cost per hour needed, when the HAPS is flying outside a MA, while C_{in} is the cost per hour needed when the HAPS is inside a MA. The higher operation cost inside a MA results from the use of mission camera and the data communication with the ground control station. The hourly cost needs to be multiplied by the total mission duration, i.e. $t_{\text{out},i}$ for the travel time outside the mission area and $t_{\text{in},i}$ for the time spent in a mission area.

In this study, the durations t_* are computed using the waypoints determined by the flight path planner described in section 4.2 and the predicted ground speed of the HAPS that is computed using the latest forecasted wind velocity. It is important to note that the planner described in Section 4 is an offline planner, i.e. the weather information used for planning is acquired before the planning process begins. Since the forecast of wind velocity vectors can vary and are unlikely to be identical to the forecast at planning time, the computed durations t_* can differ from the estimated durations given by the MMS.

The total profit of a plan $f_{\text{profit}}(plan)$ is calculated as the sum of the profit for each MA_i, $i \in \{1, \ldots, n_{\text{MA}}\}$.

5.1.2. Risk

The risk is determined by the probability of a crash. The HAPS may crash due either to a collision with a no-go area with hazardous weather or an energy deficiency. However, the latter is ignored in this work since we focus only on the mission operation during daylight.

The risk objective function of a plan $f_{\text{risk}}(plan)$ has the following form:

$$
\begin{aligned}
f_{\text{risk}}(plan) &= \text{P}(\text{Collision}) \\
&= 1 - \text{P}(\nexists \text{ Collision}) \\
&= 1 - \textstyle\bigcap_{t=1}^{t_n} \text{P}_t(\nexists \text{ Collision}) \\
&= 1 - \textstyle\bigcap_{t=1}^{t_n} \bigcap_{obs=1}^{obs_n} \text{P}_{t,obs}(\nexists \text{ Collision}) \\
&= 1 - \textstyle\bigcap_{t=1}^{t_n} \bigcap_{obs=1}^{obs_n} \left(1 - \text{P}_{t,obs}(\text{Collision})\right),
\end{aligned} \tag{5}
$$

where t_n is the total number of discretized time instances of a plan, and obs_i are the obstacles or rather no-go areas that can be encountered.

Let d be the minimum distance of the HAPS from a given obstacle. The risk of colliding with the obstacle is defined by

$$P_{t,obs}(\text{Collision}) = e^{-\lambda(d-d_{\min})}, \tag{6}$$

if $d > d_{\min}$ or otherwise, $P_{t,obs}(\text{Collision}) = 1$.

Eq. 6 dictates that the closer the platform is to a no-go area (obs), e.g. a cumulonimbus cloud, the higher the risk of a damage or a crash. In the decision assistant, a minimum safety distance $d_{\min}$ is defined and can be altered by the operator. The factor $0 < \lambda < 1$ is predefined and depends on the airspeed and turning radius of the HAPS.

5.2. Analytical Selection of the 'Best' Plan

Equations (4) and (5) return a profit and risk for every plan suggested by the planner. The operator is interested in minimizing risk and maximizing profit simultaneously. Only in the rarest cases, a plan attains the maximal reward and the minimal risk, hence complicating the operator's task to select the best plan. In most cases, the operator needs an analytical ranking of the plans.

The aim is to find the 'best' plan while regarding the two criteria: profit and risk. In general, these two criteria could be in conflict with each other and an appropriate trade-off between reward and risk has to be considered while selecting the 'best' plan. The DA is intended to help the operator decide for the best plan.

The decision making is done in two steps: filtering and ranking. In the filtering step, the operator enters a value for the minimum profit $P_{\min}$ and a value for the maximum risk $R_{\max}$.These hard constraints work as a selection filter. Only plans that fulfil these constraints are ranked, as shown in Fig. 5. Subsequently, the soft constraints (maximum reward and minimum risk) are evaluated. For each plan the two-dimensional weighted Euclidean distance [5] to the point $P = (P_{\min}, R_{\max})$ has to be calculated with the following:

$$d(P, Plan_i) = \sqrt{\left(d_{\text{profit}}\omega_{\text{profit}}\right)^2 + (d_{\text{risk}}\omega_{\text{risk}})^2}, \tag{7}$$

where the indices i stands for the index of feasible plans. The plan with the maximum weighted distance to the lower threshold (point P) represents the 'best' of the suggested feasible plans. The difference between $P_{\min}$ and the profit of the i-th plan, is denoted by d_{profit}. Similarly, the difference between $R_{\max}$ and the risk of the i-th plan, is represented by d_{risk}.

The weight factors ω_{profit} and ω_{risk} are used because of the different units of the contributing factors in the objective function: risk in percentage and profit in Euro. The weights can also be adapted by the operator, depending on how safety-oriented he is. With the variable weight ω_{risk}, (Eq. 5) the operator can define the effect of the risk for the overall ranking result. Typically, the smaller the value of ω_{risk} is, the more risk seeking is the operator. In contrast, the higher ω_{risk} is, the more safety-oriented is the operator.

The following flow chart in Fig. 5 gives an additional overview of the running decision assisting process. At first the DA receives the suggested plans, formatted in one XML data, and the current weather updates. With this information, the profit and risk value of each plan will be calculated. The next steps is to review the returned profit and risk values by the operator. If the operator needs more support to find the 'best' plan, as described above, the selection filter is used and afterwards the plans are compared again including the ranking with Eq. 7.

5.2.1. Implementation of the Decision Assistant

An example profit-risk analysis for the computed plans is shown in Fig. 6 with the exact values of the output shown in Fig 8. The axes represent the two objective functions: profit (vertical axis) and risk (horizontal axis). Each point in the figure depicts the computed profit and risk of one plan.

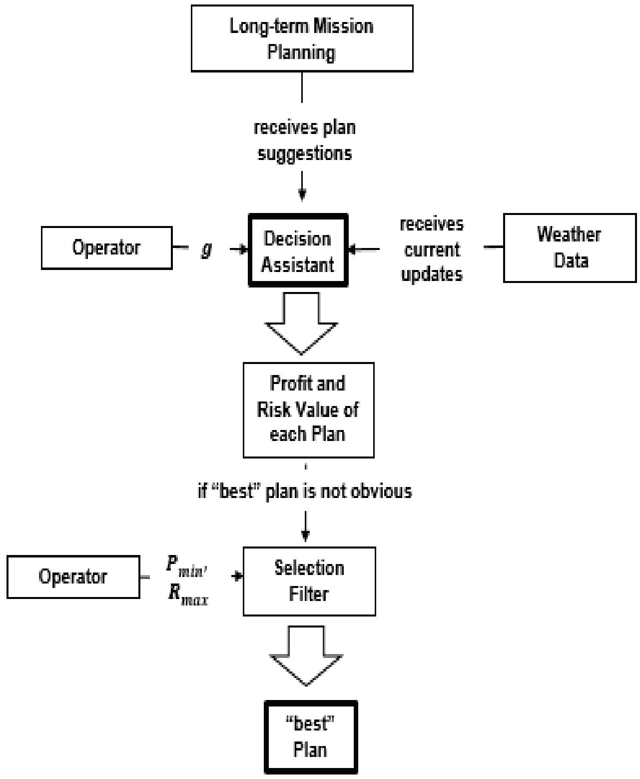

FIGURE 5. Decision making process for the search of the 'best' plan

It is evident that Plan 4 has the highest profit (128235 €) and the most substantial risk (0.793) values and Plan 1 has the lowest profit (46885€) but therefore the lowest risk value (0.00001). It is hence not intuitive to a human operator to select the best plan without an analytical tool.

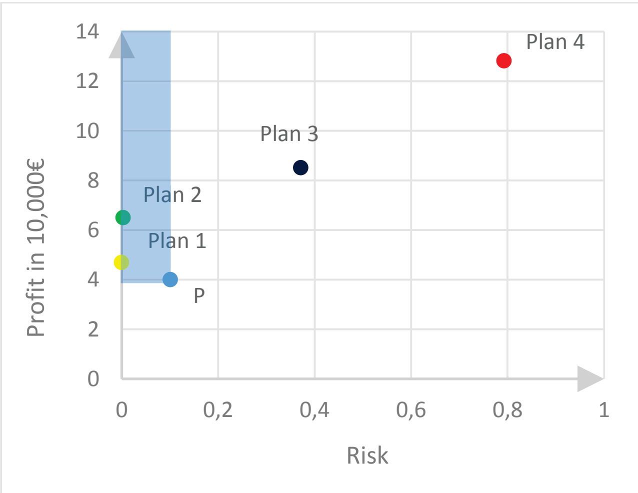

FIGURE 6. Profit - Risk graph

The profit and risk of the plans as shown in Fig. 6 are calculated using selected parameters shown in Tab. 2. For the example mission described in section 2, four plans were generated and evaluated, although the hierarchical scheduler/planner can generate more plans, to the detriment of the computation time.

In this case shown in Fig. 6, there is no plan which has the maximum profit with the minimum reward. As mentioned in the previous subsection, the operator defines the acceptable thresholds ($P_{\min}, R_{\max}$). These thresholds are used to filter out plans, as shown in Fig. 6 with the shaded region and subsequently, Eq. 7 is used to rank the remaining plans. Using the parameters in TAB 2, plan 3 is the 'best' solution.

Variables	Values
λ	0.000247937
C_{out}	1000 €
C_{in}	1500 €
v^a	30 m/s
$P_{\min}$	50000 €
$R_{\max}$	0.4
ω_{risk}	278713.6

TAB 2. Parameters used for test implementation

6. HUMAN MASCHINE INTERFACE

The human-machine interface (HMI) on the ground control station is supposed to provide the HALE crew with information about the weather conditions around the UAV and the geographic environment. Its main interface is equipped with a map that displays the weather situation, as shown in Fig. 7.
The scope of the mission planning involves operations at a constant flight level of 18-20 km. In order to maintain its altitude, the HALE avoids horizontally zones with critical weather conditions. Therefore, the user interface displays information only on a two-dimensional map, because the altitude change of the HAPS is negligible compared to the horizontal position change. For example, on the map shown in Fig. 6, the following weather data are displayed:

1. Wind velocity in form of wind barbs,
2. Cb-LIKE Clouds, in form of red polygons.

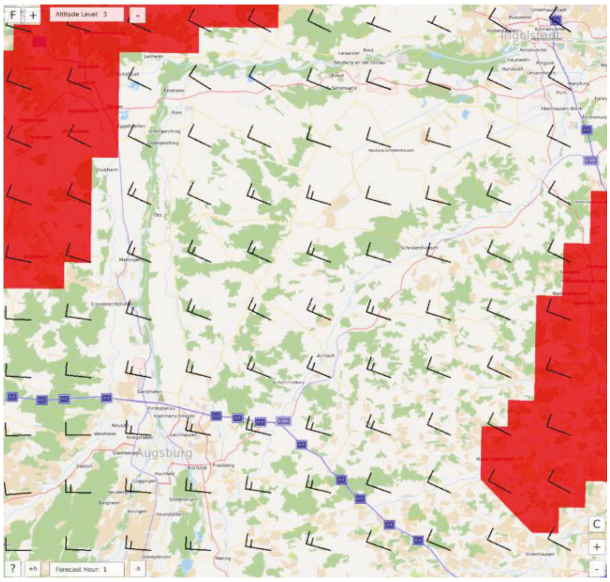

FIGURE 7. Visualization of weather data (Cb-LIKE and wind velocity) on the HMI

Showing all available weather information listed in Tab. 1 at the same time will be overwhelming for the operator. Therefore, it is more reasonable to show only weather information that is necessary. Forecast time and altitude level can be selected by the operator (upper left corner and lower left corner respectively).

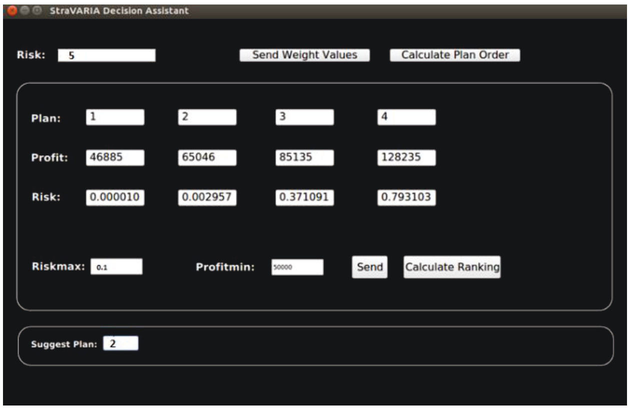

FIGURE 8. Interface of the decision assistant

The graphical user interface (GUI) of the DA (Fig. 8) is realised as an interactive add-on side screen window, which can be launched if the operator needs it. As described earlier, the DA returns an overview of calculated profit and risk. The operator can now decide if more support is needed to make a decision or if the 'best' plan is clear to be selected directly without further analysis. If more support is needed, the operator first enters the desired maximum risk and minimum profit to filter suggested plans that do not fulfil these requirements. Subsequently, the operator provides the risk weight factor ω_{risk} of the total weighted objective function (Eq. 7).

7. CONCLUSION

This article presents a mission management system for a HALE with a primary focus on dealing with highly dynamic weather data. Designed to support the operation crew, the management system complies with the aviation abilities of the chosen HAPS. To create a realistic mission scenario, we implemented real weather data that includes wind, cloud coverage, turbulences and thunderstorms. Using an example mission scenario in the Bavarian region, we tested the feasibility of the concept developed for the MMS. Multiple flight plans are computed by the hierarchical scheduler/planner. The operator is required to make the final decision by selecting the 'best' plan among the suggestions. We developed a decision assistant that compares the profit and risk of all plans. An advantage of the decision assistant is the possibility to rank the suggested plans interactively, by adapting to different weight factors imposed by the operator. This makes it possible to respond effectively to situation changes.

Another outcome of this work is the integration of weather data in the human machine interface. The HMI provides a weather situation map, which ensures an overview of the current and future situation in the vicinity of the HAPS. In summary, it can, therefore, be said that by the usage of the described MMS reduces the workload of the operation crew and subsequently, operation costs can be saved without compromising safety.

Further research work could focus on the integration of live weather data recorded by on-board sensors to help the HAPS react to hazards. Another interesting work would be to consider a mission scenario with multiple HAPS.

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